Research Article

Multimodal Visual Quality Evaluation of Dadih from Java and Sumatra Using Deep Learning-Based Electronic Eye, CIELab Colorimetry, and Sensory Analysis

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Abstract | Dadih is a traditional fermented milk product widely produced in West Sumatra, Indonesia, characterised by a compact gel structure and stable visual quality. This study aimed to develop a multimodal evaluation framework integrating a deep learning–based electronic eye (e-eye) and CIELab colourimetry to assess and benchmark dadih produced in Java against West Sumatran references. Four treatments were analysed, including two reference samples (T1 and T2) and two Java-produced samples (T3 and T4). The data were analysed using one-way ANOVA followed by Duncan's multiple range test (DMRT) ($p < 0.05$), while visual classification was performed using a convolutional neural network (CNN) trained on 400 images (100 per class) with an 80:20 training–validation split and data augmentation, achieving a classification accuracy of 98%. T2 exhibited the highest lactic acid bacteria count (8.10 $\log_{10}$ CFU/g), titratable acidity (15.00 g/100 g), and lowest pH (3.80), while T4 showed the highest water activity (0.913) and lowest acidity (8.00 g/100 g). The CNN classified T1 as "Excellent", T2 as "Good", T3 as "Fair", T4 as "Poor", aligned with sensory and colourimetric results. These results suggest that dadih from West Sumatra can serve as a reliable reference for good quality, while dadih produced in Java still needs better control during fermentation. Maintaining temperatures around 30–37°C and allowing fermentation to proceed for approximately 24–48 hours can improve acidity, microbial activity, and gel structure. Overall, the proposed multimodal approach provides a practical and objective framework for standardising the quality of fermented dairy products.

Keywords | Dadih; fermented milk; deep learning; electronic eye; cielab colorimetry; color analysis

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INTRODUCTION

Dadih is a traditional Indonesian fermented milk product predominantly produced in West Sumatra through spontaneous fermentation in bamboo containers (Anindita *et al*., 2026; Pramana *et al*., 2025). This process produces a compact gel structure with a relatively uniform appearance and distinct physicochemical properties. The development of dadih production outside its traditional region, including in Java, is partly influenced by limited availability and the relatively high cost of distribution. Previous work has shown that dadih can be successfully produced beyond its area of origin, such as in Taiwan (Wati *et al*., 2022). In this context, the present study explores its production in Java to improve accessibility and broaden its consumption. These variations can influence structural stability, colour characteristics, and syneresis behaviour, thereby affecting the visual quality of the final product (Wang *et al*., 2023). However, evaluation of dadih quality remains largely dependent on sensory judgement, which is subjective and lacks reproducibility (Ramaiyulis *et al*., 2021).

Previous studies have applied sensory evaluation and instrumental techniques, such as CIELab colourimetry, to assess fermented dairy products. While sensory analysis reflects human perception, it is prone to bias, whereas instrumental methods provide quantitative measurements but are unable to capture complex visual features such as surface texture and structural defects (Buckley and Giorgianni, 2023; Sirisathitkul *et al*., 2025). Recent advances in artificial intelligence and computer vision have enabled the development of electronic eye (e-eye) systems capable of extracting complex visual features and performing automated classification (Khalifa and Albadawy, 2024; Trigka and Dritsas, 2025). However, their application in traditional fermented products such as dadih remains limited.

Existing studies remain limited, as they mainly focus on single evaluation approaches without integrating multiple analytical dimensions. A multimodal evaluation approach, combining sensory analysis, instrumental colourimetry, and AI-based visual assessment, offers a more comprehensive strategy for evaluating dadih quality. This study aimed to develop and apply a multimodal evaluation framework integrating a deep learning–based e-eye, CIELab colourimetry, sensory analysis, and physicochemical and microbial parameters to assess and benchmark dadih produced in Java against reference samples from West Sumatra. It was hypothesised that the integration of AI-based visual analysis with conventional methods would provide a more objective and reliable evaluation of dadih quality and reveal differences between production regions.

MATERIALS AND METHODS

Preparation of java dadih

Java dadih was made using bovine colostrum that was freshly collected in the early milking period (Figure 1) after parturition and its physicochemical properties are listed in Table 1. The h typical of classic buffalo milk-based dadih as well as increase nutritional value owing to its high protein and bioactive compound content. Before fermentation, the nutritional content of colostrum (fat, protein, lactose and total solids) was analysed by creamery method using a Lactoscan milk analyser. It should be noted that bovine colostrum differs substantially from buffalo milk in composition, which may affect fermentation behaviour and structure. This difference represents a potential confounding factor; therefore, the results should be interpreted as product-based comparisons rather than direct equivalence of raw materials. To avoid undesirable microbial contamination but also preserve functional components, samples were filtered as described above and pasteurised at 85 °C for 30 minutes before fermentation. In addition, the use of pasteurised colostrum in Java samples and raw milk in traditional samples represents different processing conditions; thus, the observed differences reflect combined effects rather than isolated variables. The colostrum was transferred directly into sterilised bamboo containers after pasteurisation to mimic conditions for fermentation used traditionally. No commercial starter culture was supplemented and spontaneous fermentation by endogenous lactic acid bacteria could occur. Samples were incubated at room temperature (28–32 °C) for 33 h until a gel with coagulated structure was formed. Fermented samples were kept at 4 °C until analysis. The fermentation containers were made of bamboo native to Java, including bamboo apus *(Gigantochloa apus)* and bamboo ori *(Bambusa blumeana)*. These species were chosen since they are very common and have been used in the past for food processing in that region, so the fermentation process could mimic traditional production practices.

Figure 1: Physical appearance of pasteurised bovine colostrum.

Sample cllection and transportation from sumatera

Dadih samples were obtained from two different producers located in West Sumatra, Indonesia. The samples were carefully packaged and transported to the research laboratory at Universitas Brawijaya, Kediri, Indonesia. The shipping duration was approximately 2–3 days. During transportation, samples were stored in insulated containers with ice packs, maintaining a temperature range of approximately 4–10°C to minimise further fermentation and structural changes.

Table 1: Physicochemical characteristics of colostrum milk.

Parameter	Value
Temperature	32 °C
Freezing point	-0.722 °C
Solid Non Fat	8.6 %
Fat	6.28 %
Density	1.061 g/mL
Protein	3.94 %
Adding Water	0 %
Lactose	5.90 %
Solid	10.74 %

Source: Author's experimental data obtained using lactoscan milk analyser.

Multimodal visual quality evaluation framework of dadih

The integrated approach used to evaluate the visual quality of dadih through three complementary methods: sensory analysis, CIELab colorimetry, and deep learning based e-eye is presented in Figure 2. Sensory analysis represents human visual perception, where visual stimuli from dadih are captured by the eye, transmitted through the retina and optic nerve, and interpreted by the brain to generate sensory perception. CIELab colorimetry provides objective colour measurement using instrumental analysis to quantify L*, a*, and b* values under controlled calibration conditions. Meanwhile, the deep learning–based (e-eye) utilises digital image acquisition and convolutional neural network (CNN) modelling to extract visual features and perform automated quality classification (Wang *et al*., 2023; Young *et al*., 2024). Together, these approaches form a multimodal evaluation framework that integrates human perception, instrumental colour measurement, and artificial intelligence–based image analysis to achieve comprehensive and objective assessment of dadih visual quality.

Electronic eye–based visual quality analysis

Visual quality of dadih was evaluated using a deep learning–based e-eye system. This approach is based on computer vision techniques, which have been widely applied in food quality assessment to extract visual features such as colour, texture, and surface characteristics in an objective and reproducible manner (Zhao *et al*., 2025; Kumar *et al*., 2026). Digital images of dadih samples from Java and Sumatra were captured under controlled lighting conditions using a fixed camera setup to ensure consistency. All images were pre-processed through resizing and normalisation prior to analysis.

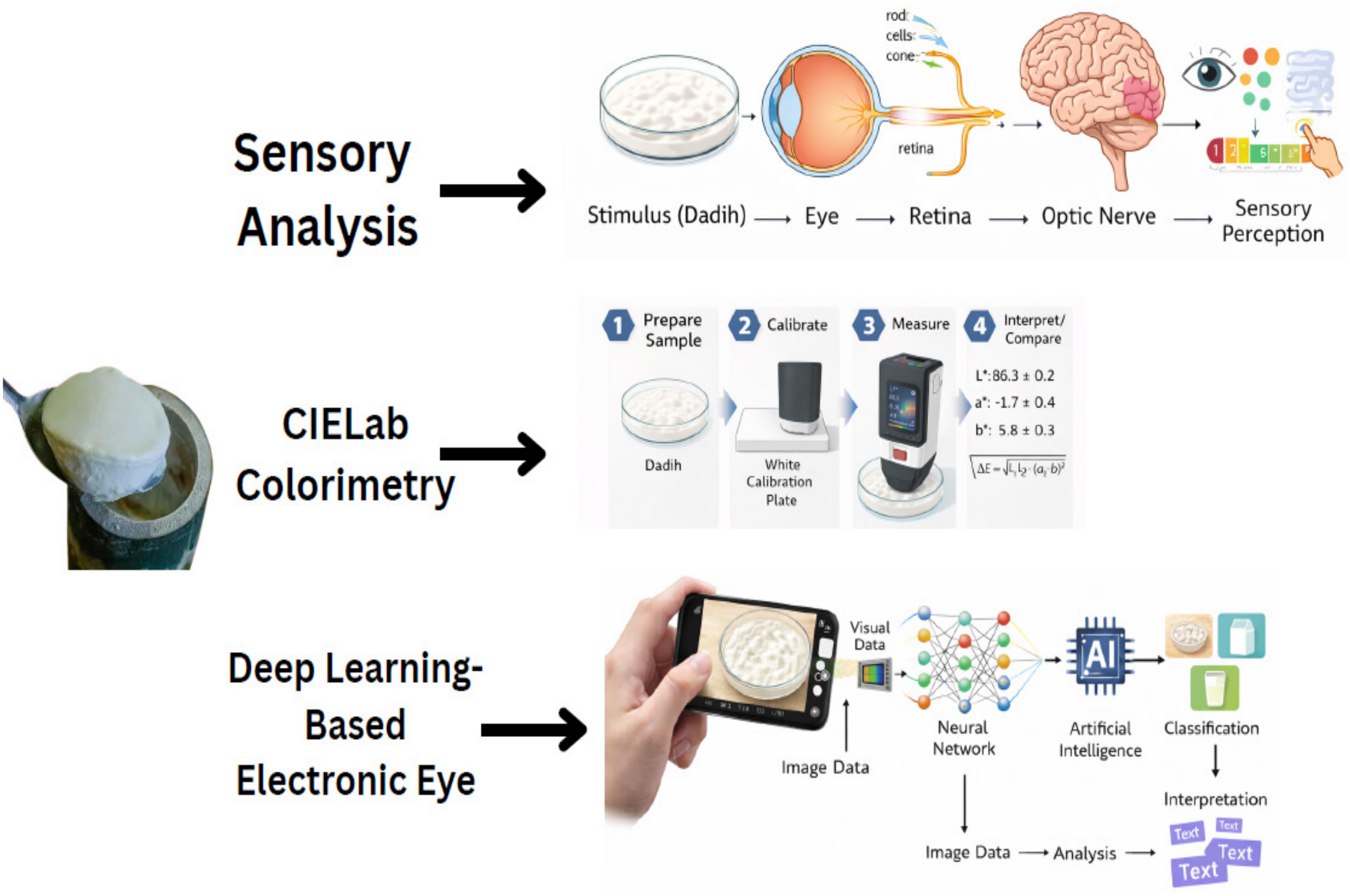

Figure 2: Integrated visual quality assessment of dadih using sensory, colorimetric, and AI-based approaches.

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A convolutional neural network (CNN) was employed due to its capability to automatically learn hierarchical visual features and perform accurate image classification without manual feature extraction (Singh and Sabrol, 2021). The CNN model was developed to classify dadih images into predefined visual quality classes (A–D). The four visual quality classes (A-D) were determined based on observable characteristics of dadih, particularly colour uniformity, gel structure, surface appearance, and the extent of whey separation (syneresis) (Arnold *et al*., 2021). The classification criteria were based on key visual indicators commonly used in fermented dairy evaluation, including colour uniformity, gel structure integrity, and whey separation, which are closely associated with product stability and fermentation performance. The dataset was divided into training and validation sets for supervised learning and model evaluation. Classification results generated by the e-eye system were visualised and subsequently compared with CIELab colourimetric measurements and sensory analysis as part of a multimodal quality assessment. The dataset was divided into 80% training and 20% validation sets using a hold-out validation approach. The CNN architecture consisted of multiple convolutional layers (Conv2D) with increasing filter sizes (32, 64, and 128), followed by max-pooling layers, a fully connected dense layer with 128 neurons, and a dropout layer (rate = 0.4) to reduce overfitting. A softmax activation function was applied in the output layer for four-class classification. The model was trained using the Adam optimizer with a learning rate of 0.0001 and a batch size of 32. Model performance was evaluated using accuracy, classification report, and confusion matrix to assess classification reliability.

All convolutional layers were configured with 3 × 3 kernels, a stride of 1, and same padding. The total number of trainable parameters was obtained from the model summary during training. To account for variations in image acquisition, several data augmentation techniques were applied, including rotation (up to 25°), width and height shifts, shear, zoom, and horizontal flipping. These transformations were intended to reflect typical variations encountered during manual image capture and to enhance model robustness. The model was trained using a hold-out validation scheme, with 80% of the data used for training and the remaining 20% for validation, without applying cross-validation due to the limited size of the dataset.

Figure 3 shows that training accuracy increased from around 0.28 to 0.85, while validation accuracy rose more quickly and reached 0.95–0.99. Training was limited to 10 epochs to avoid overfitting, considering the relatively small dataset size. The higher validation accuracy, especially at the early epochs, may indicate that the validation data were less complex or easier to distinguish visually than the training data. This suggests that the model was able to capture key visual patterns, but it may also reflect differences in the data distribution. Training loss decreased from approximately 1.5 to 0.40–0.50, while validation loss dropped to around 0.30, with only a small gap between the two curves. This indicates that the optimisation process was generally stable. However, the difference between training and validation accuracy should be interpreted carefully, as it may be influenced by differences in data complexity rather than solely by model performance. Overall, the model was able to learn relevant visual features, although further evaluation using more balanced data would help confirm the robustness of the results.

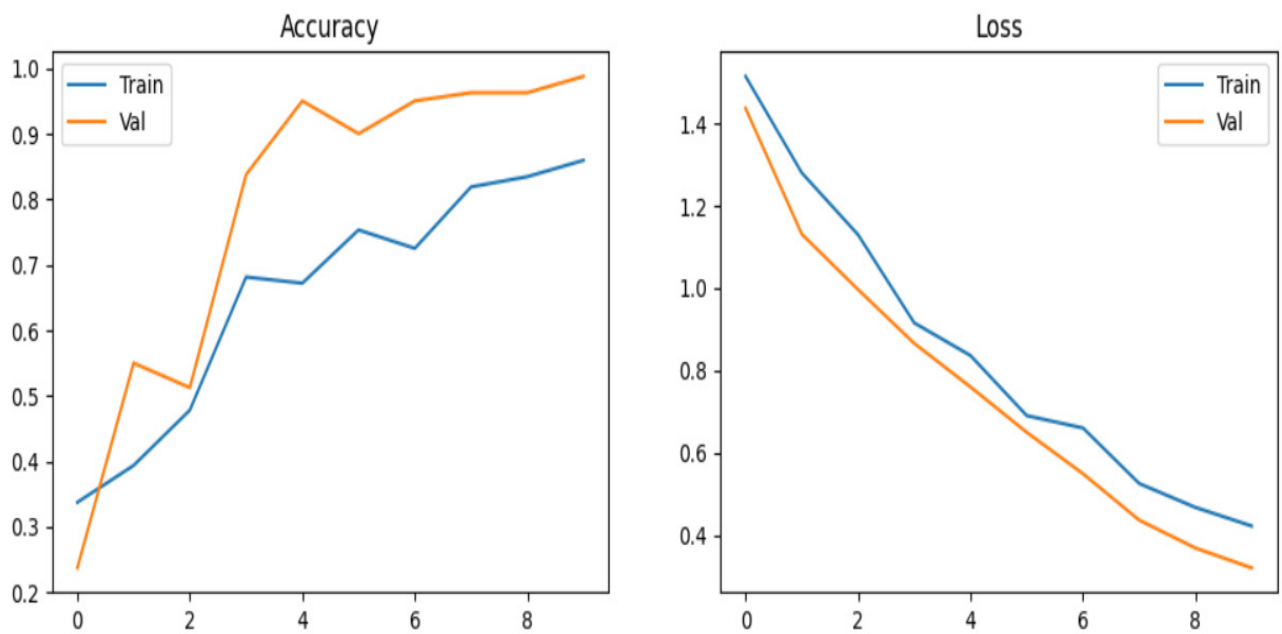

Figure 3: Training and validation accuracy and loss curves of the CNN-based (e-eye) model across epochs.

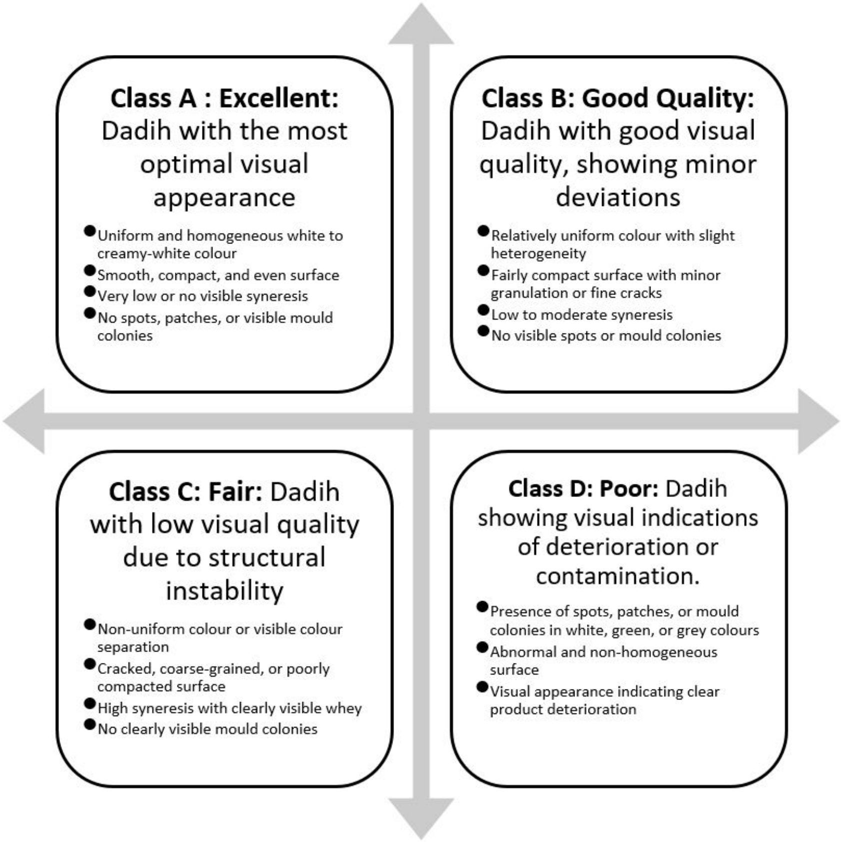

Figure 4: Classification framework for dadih visual quality using a deep learning–based (e-eye) system.

The figure illustrates a conceptual grading framework for dadih visual quality supported by a deep learning–based (e-eye) system, as shown in Figure 4. The classification structure organises products into four hierarchical quality tiers based on progressively changing visual indicators such as surface stability, moisture release, colour consistency, and signs of deterioration (Tamime and Robinson, 2007; Lucey, 2002; Herlina and Setiarto, 2024). The upper categories represent structurally stable and visually uniform products, whereas the lower categories reflect increasing structural defects and contamination risk. This framework demonstrates how artificial intelligence can translate visual features into standardised quality levels, enabling objective and reproducible assessment of traditional fermented dairy products.

Cielab colorimetry

Approximately 10 g of dadih was placed in a Petri dish with a leveled surface. The colorimeter was switched on and set to the CIELab color space (L*, a*, b*). The sensor was positioned perpendicular to the sample surface to obtain L*, a*, and b* values (Buckley and Giorgianni, 2023). Measurements were performed in triplicate for each treatment to ensure accuracy, and the recorded values were expressed as the mean ± standard deviation. The data were statistically analyzed using one-way analysis of variance (ANOVA) at a 5% significance level ($p < 0.05$). When significant differences were detected, Duncan's Multiple Range Test (DMRT) was applied to compare means among treatments.

Sensory evaluation

Sensory evaluation was conducted to assess the visual quality of dadih samples from four treatments (T1–T4) using 20 semi-trained panelists under controlled laboratory conditions. Approximately 30 g of each sample was placed in identical transparent containers, coded with random three-digit numbers, and presented at room temperature (28–32 °C) under uniform white lighting. The evaluated attributes included syneresis intensity, distribution of surface whey, colour, colour and structural uniformity, overall appearance, and overall liking. Each attribute was assessed using a structured 5-point scale (1 = very poor/very low/strongly dislike; 5 = very good/very high/strongly like). The scoring criteria were clearly defined, ranging from absence to dominance of surface whey for syneresis-related parameters, from very dull to very bright for colour, from highly non-uniform to highly uniform for structural consistency, and from very unattractive to very attractive for overall appearance (Arilla *et al*., 2023). Overall liking was measured using a 5-point hedonic scale from strongly dislike to strongly like. Samples were evaluated independently in randomized order, and the results were expressed as mean scores and analyzed using ANOVA followed by Duncan's multiple range test at $p < 0.05$.

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PH measurement

The pH of dadih was measured using a pH meter that had been calibrated with standard buffer solutions at pH 3.0 and 7.0. Prior to measurement, 5 mL of sample was diluted with 10 mL of distilled water and homogenised for 5 minutes to ensure uniformity (Melia *et al*., 2021).

Titratable acidity determination

Titratable acidity was assessed by transferring 10 mL of the sample into a glass beaker using a volumetric pipette. After adding a few drops of phenolphthalein indicator (Sigma-Aldrich, USA), the sample was titrated with 0.1 M NaOH until a persistent pale pink endpoint was reached (Melia *et al*., 2021).

Enumeration of lactic acid bacteria, yeast, and mould

Microbial counts were assessed by first homogenising 25 g of dadih with 225 mL of sterile 0.85% (w/v) sodium chloride solution (Merck, Germany) for 10 min using a magnetic stirrer to obtain a uniform suspension. Serial dilutions were subsequently prepared in the same diluent and spread onto selective culture media. Lactic acid bacteria were enumerated on de Man–Rogosa–Sharpe (MRS) agar (Oxoid, United Kingdom), whereas yeast and mould populations were determined using Potato Dextrose Agar (PDA) (Oxoid, United Kingdom) (Phovisay *et al*., 2024).

RESULTS AND DISCUSSION

CNN-based classification performance of dadih visual quality

Figure 5 presents the confusion matrix of the CNN-based (e-eye) model for dadih quality classification. Darker colour indicates a higher number of samples in each cell. The matrix shows perfect diagonal dominance, with all samples correctly classified into their respective categories (A_Excellent), (B_Good), (C_Fair), (D_Poor), and no misclassification observed across classes. Specifically, the model correctly identified 100 samples of Class T1, 100 samples of Class T2, 100 samples of Class T3, and 100 samples of Class T4, yielding an overall test accuracy of 98%. This performance can be attributed to the distinct visual differences among treatments, where samples such as T1 and T4 exhibited clear contrasts in colour and gel structure, allowing the model to distinguish classes effectively. In addition, data augmentation and the use of regularisation layers (Dropout and MaxPooling) were applied to reduce the risk of overfitting and improve model generalisation. Data augmentation was applied using ImageDataGenerator, including rotation (up to 25°), width and height shifts, shear transformation, zoom, horizontal flipping, and pixel rescaling (1/255) to enhance dataset variability. Nevertheless, it is important to note that model performance may vary when applied to external datasets, particularly those obtained under different lighting conditions or background settings compared to the controlled laboratory environment used in this study.

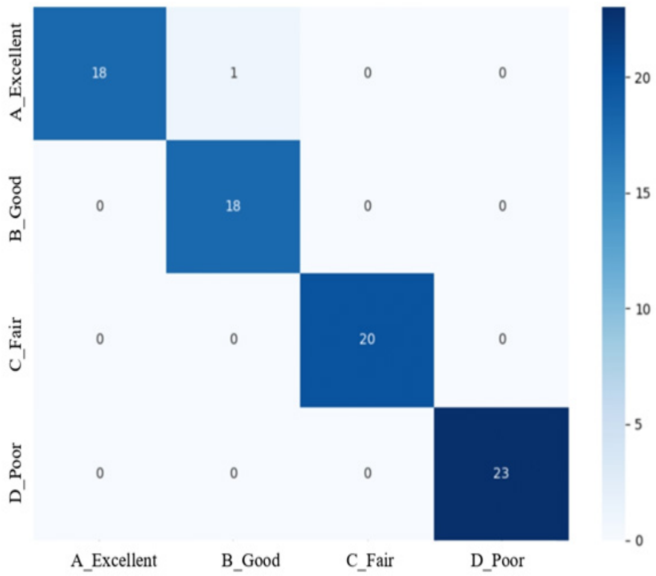

Figure 5: Confusion matrix analysis.

Visual characteristics of dadih from different producers and bamboo types

Figure 6 presents the visual appearance of dadih samples produced using different bamboo types and milk sources. Noticeable differences were observed in surface structure, colour tone, and whey separation among treatments. Samples obtained from traditional producers in West Sumatra exhibited more uniform gel structure and compact appearance, while experimentally prepared dadih showed variations in surface smoothness and whey distribution depending on the bamboo type used (ori and apus). These visual differences suggest that raw material composition and fermentation container may influence the structural integrity and overall appearance of dadih; however, the potential effects of transportation cannot be completely excluded.

Control sample description and classification criteria

The control sample used in this study consisted of commercially available dadih widely distributed in West Sumatra, Indonesia. Traditionally produced using fresh buffalo milk and spontaneous fermentation in bamboo containers, West Sumatran dadih is typically characterised by a bright white to slightly creamy colour, a compact and cohesive gel structure, and a relatively smooth surface with minimal whey separation (Anindita *et al*., 2026; Herlina and Setiarto, 2024). The product generally exhibits a dense,

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spoonable consistency with a mildly acidic aroma and uniform appearance, reflecting stable fermentation and well-developed protein coagulation (Pramana *et al*., 2025). In the present study, this commercially established product was used as a visual reference standard in the (e-eye) –based classification system. To ensure objective categorisation, the visual quality grading followed predefined classification rules:

- Class A (Excellent): Stable gel structure, uniform colour, minimal or no whey separation, and highly attractive appearance.
- Class B (Good): Minor visual imperfections, slight whey presence, but overall structural integrity maintained.
- Class C (Fair): Noticeable structural breakdown accompanied by dominant whey release and reduced visual uniformity.
- Class D (Poor): Assigned when visible mould colonies or contamination spots are present on the surface. If no mould is detected, classification is based on structural and visual integrity:

(a) Dadih shipped from producer 1 (b) Dadih shipped from producer 2

(c) Dadih prepared from cow's milk and fermented in bamboo ori, (d) Dadih prepared from cow's milk and fermented in bamboo apus

Figure 6: Samples of dadih produced using different bamboo types and milk sources.
Source: Personal documentation.

Prediction : Good
Accuracy : 0.6066
Class probability:
Excellent: 0.6066
Good : 0.3902
Fair: 0.0017
Poor: 0.0015

Figure 7: CNN-Based (e-eye) Classification of Control Dadih Sample from West Sumatra.

The numerical values represent the class probability outputs generated by the CNN-based (e-eye) system for visual quality classification, as presented in Figure 7. The model classified the sample as “Good” with a confidence level of 0.7644 (76.44%), indicating that this category had the highest predicted probability among all classes. The remaining values correspond to the likelihood of the sample belonging to other quality categories, including “Excellent” (0.7795) and lower-quality classes with substantially smaller probabilities. These probabilities are derived from the softmax function and reflect the model’s level of certainty in assigning the sample to a specific visual quality class.

Treatment 1	
	Prediction : Excellent Accuracy : 0.7795 Class probability: Excellent: 0.7795 Good : 0.2083 Fair: 0.0065 Poor: 0.0056
Treatment 2	
	Prediction : Good Accuracy : 0.7644 Class probability: Excellent: 0.2153 Good : 0.7644 Fair: 0.0139 Poor: 0.0063
Treatment 3	
	Prediction : Fair Accuracy : 0.6423 Class probability: Excellent: 0.0047 Good : 0.0033 Fair: 0.3497 Poor: 0.6423
Treatment 4	
	Prediction : Poor Accuracy : 0.8808 Class probability: Excellent: 0.0039 Good : 0.0088 Fair: 0.1066 Poor: 0.8808

Figure 8: CNN-Based (e-eye) classification results of dadih samples across treatments.

Electronic eye evaluation of dadih visual quality

The CNN-based (e-eye) demonstrated clear differentiation among treatments based on visual characteristics, as shown in Figure 8. The model was developed using a sequential Convolutional Neural Network (CNN) architecture consisting of multiple Conv2D layers (32, 64, and 128 filters), followed by MaxPooling, a fully connected Dense layer (128 neurons), and a Softmax output layer for four-class classification. The dataset comprised 400 images (100 per treatment), which were split into 80% training and 20% validation subsets using a hold-out validation approach, with data augmentation applied to enhance generalization. The model achieved a high classification accuracy of approximately 98% on the validation set; this near-perfect performance may be attributed to clearly distinguishable visual differences among treatments, particularly in colour contrast and whey separation. The higher validation accuracy compared to training accuracy in early epochs may indicate differences in dataset complexity or distribution, suggesting that further dataset balancing and validation strategies are required.

Treatment 1 was classified as “Excellent” with a high confidence level (0.7795), indicating strong visual conformity to the optimal criteria, such as uniform colour distribution and stable gel structure. Treatment 2 was categorised as “Good” (0.7644), reflecting minor visual imperfections but overall acceptable structural integrity. In contrast, Treatments 3 and 4 were classified as “Fair” and “Poor” with high confidence (0.6423 and 0.8808), indicating visible structural instability and whey separation. These classification categories were defined based on observable visual indicators, including colour uniformity, gel consistency, and whey release, which are commonly used as qualitative indicators of fermented dairy product quality.It is important to note that the confidence values derived from the Softmax output represent the model’s prediction probability rather than statistical significance. Therefore, these results were further supported by evaluation metrics such as classification accuracy and validation performance, ensuring the robustness of the model. Moreover, the visual classification results were aligned with physicochemical and sensory observations, where treatments with higher structural stability and lower whey separation corresponded to better quality classifications. This integration confirms that the CNN-based e-eye system is capable of capturing meaningful visual features that align with conventional quality parameters. These confidence values do not represent population-level statistical significance or model generalisation, as no independent test set or confidence interval analysis was performed. Therefore, the interpretation of results is limited to prediction probabilities and model performance within the available dataset.

CIELAB COLOUR PROFILE OF DADIH ACROSS TREATMENTS

The CIELab analysis revealed significant differences ($p < 0.05$) in colour parameters among treatments, as determined by one-way analysis of variance (ANOVA) followed by Duncan's multiple range test. The data are presented as mean ± standard deviation. These results indicate that both milk source and fermentation container influenced the visual appearance of dadih. The detailed values of L*, a*, and b* are presented in Table 2. Treatment 3 exhibited the highest lightness value (L* = 91.23 ± 0.29^{a}), which was significantly higher ($p < 0.05$) than those of other treatments, indicating a brighter and more visually luminous product. In contrast, Treatment 2 showed the lowest L* value (81.83 ± 1.15^{d}), suggesting a relatively darker appearance. The higher brightness observed in T3 may be associated with differences in protein matrix structure and moisture distribution, which influence light reflectance on the gel surface (Rachmawati *et al.*, 2022). However, its classification as fair by the CNN indicates that visual quality is not determined by colour alone. The model likely captured structural issues such as uneven surface, whey separation, and weak gel formation despite the high brightness value. Redness (a*) values were markedly higher in T1 (6.13 ± 0.15^{a}), indicating a stronger red/yellowish tone, whereas T3 showed values close to neutral (0.13 ± 0.06^{d}), suggesting a whiter and less pigmented appearance. Similarly, yellowness (b*) was highest in T1 (31.03 ± 0.40^{a}) and lowest in T4 (14.60 ± 1.23^{c}). Elevated a* and b* values in T1 may reflect differences in raw milk composition, fat content, or fermentation-induced pigment changes. The high L* value in T3 (91.23) indicates a brighter colour. Meanwhile, lower b* values in T3 and T4 indicate reduced yellow intensity. When compared with the CNN-based (e-eye) classification results (Figure 8), a aligned pattern emerges. Treatment 1, which showed relatively balanced colour intensity and moderate brightness, was classified as "Excellent" with high confidence, indicating strong visual conformity to premium quality criteria. Treatment 2, despite having lower lightness, was classified as "Good," suggesting that minor colour variation did not substantially reduce perceived visual acceptability. In contrast, Treatments 3 and 4, which exhibited reduced colour intensity (lower a* and b* values) and altered surface characteristics, were categorised as "Fair" and "Poor" reflecting the influence of structural instability and whey separation on overall visual grading. These findings suggest that instrumental colour parameters may be associated with AI-based visual classification outcomes. However, further statistical validation, such as correlation analysis, is required to confirm the strength of this relationship. The results indicate that colour attributes potentially contribute to the differentiation of dadih quality across treatments.

Table 2: Instrumental colour characteristics of dadih measured using the cielab system.

Treatment	L*	a*	b*
T1	84.37 ± 0.50^{c}	6.13 ± 0.15^{a}	31.03 ± 0.40^{a}
T2	81.83 ± 1.15^{d}	5.10 ± 0.20^{b}	27.33 ± 0.83^{b}
T3	91.23 ± 0.29^{a}	0.13 ± 0.06^{d}	15.37 ± 0.15^{c}
T4	87.70 ± 0.53^{b}	1.03 ± 0.12^{c}	14.60 ± 1.23^{c}

Data are presented as mean ± standard deviation. Means sharing different lowercase letters within the same column differ significantly according to the DMRT test at $p < 0.05$. T1: Treatment 1 (dadih West Sumatera from producer 1), T2: Treatment 2 (dadih West Sumatera from producer 2), T3: Treatment 3 (dadih Java from ori bamboo), T4: Treatment 4: (dadih Java from apus bamboo).

SENSORY EVALUATION PROFILE OF DADIH

The radar plot (Figure 9) illustrates the comparative sensory attributes of dadih across treatments. Significant differences ($p < 0.05$), as determined by one-way analysis of variance (ANOVA) followed by Duncan's multiple range test, were observed in all sensory parameters, including syneresis intensity, surface whey distribution, colour, structural uniformity, overall appearance, and overall liking. The data are presented as mean ± standard deviation (Table 3). Treatments T3 and T4 exhibited significantly higher scores in syneresis intensity and surface whey distribution ($p < 0.05$), indicating greater structural instability and whey separation. Increased whey separation likely disrupted the compact gel matrix, leading to reduced visual appeal. In contrast, Treatments T1 and T2 showed significantly higher scores in colour, structural uniformity, overall appearance, and overall liking ($p < 0.05$), suggesting better visual quality and higher perceived acceptability based on panelist evaluation. Among all treatments, T2 consistently demonstrated the highest sensory scores, particularly in colour (4.80 ± 0.09^{a}), structural uniformity (4.90 ± 0.08^{a}), overall appearance (4.90 ± 0.09^{a}), and overall liking (4.80 ± 0.10^{a}), indicating superior sensory performance under controlled evaluation conditions. These findings are aligned with the instrumental and AI-based evaluations, where Treatments 3 and 4 were classified into lower quality categories due to structural breakdown and surface instability. The sensory results suggest that visual attributes such as surface smoothness, colour consistency, and whey presence strongly influence perceived quality. Moreover, sensory evaluation provides complementary insights beyond instrumental and AI-based analyses by capturing human perception of visual and structural quality. While instrumental and CNN-based methods quantify physical attributes, sensory assessment reflects how these characteristics are perceived under real conditions, highlighting its role in interpreting and

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validating overallproduct quality. The difference between the sensory results and the CNN classification is likely due to the different aspects assessed by each approach. Sensory evaluation reflects overall perception, while the CNN is limited to visual characteristics. In this study, T1 appeared more visually stable, whereas T2 was more preferred by the panelists, suggesting that both methods offer complementary perspectives rather than conflicting outcomes.

Microbial dynamics, acidification, and water activity of dadih

As presented in Table 3, significant differences ($p < 0.05$), as determined by one-way analysis of variance (ANOVA) followed by Duncan's multiple range test, were observed among treatments in lactic acid bacteria (LAB) counts, titratable acidity, and pH values. The data are expressed as mean ± standard deviation. Treatment 2 showed relatively higher LAB counts (8.10 ± 0.10^a), together with the highest titratable acidity (15.00 ± 0.25^a g lactic acid/100 g) and the lowest pH (3.80 ± 0.04^d).

The pronounced difference in acidity and pH suggests more extensive acid production, which plays a key role in protein coagulation and gel formation, rather than being driven by differences in LAB counts alone (Abedi and Hashemi, 2020; Balasubramanian *et al*., 2024). The stronger acidification likely contributed to the relatively compact structure observed in Treatment 2, which was classified as "Good" by the CNN-based (e-eye) and received favourable sensory scores. In contrast, Treatment 4 showed the lowest LAB count (7.30 $\log_{10}$ CFU/g), the lowest titratable acidity (8.00), and the highest pH (5.50), indicating minimal fermentation and insufficient acid development. The relatively high pH value suggests that acidification was largely incomplete, which likely hindered casein network formation and resulted in structural instability and increased whey separation (Li and Zhao, 2019; Sun *et al*., 2018). This is aligned with the sensory evaluation results, where Treatment 4 exhibited higher syneresis intensity and lower structural uniformity, as well as its classification as "Poor" by the (e-eye) system.

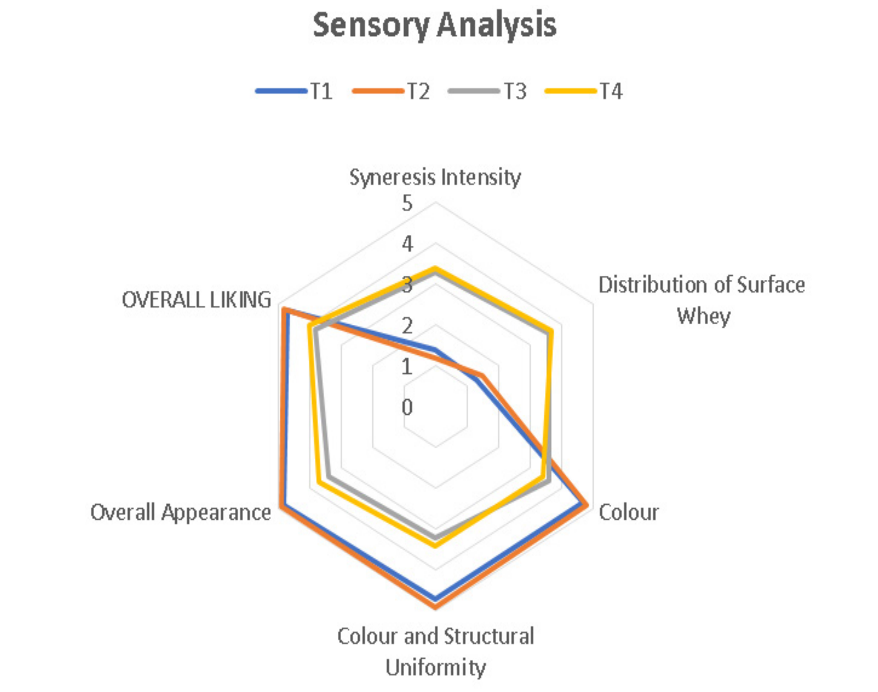

Figure 9: Radar plot representing sensory attributes of dadih.

Table 3: Comparative sensory attributes of dadih across treatments.

Treatment	Syneresis intensity	Surface whey distribution	Colour	Colour and structural uniformity	Overall appearance	Overall liking
T1	1.40 ± 0.15^b	1.30 ± 0.12^b	4.70 ± 0.10^a	4.70 ± 0.11^a	4.80 ± 0.10^a	4.70 ± 0.12^a
T2	1.20 ± 0.10^b	1.50 ± 0.13^b	4.80 ± 0.09^a	4.90 ± 0.08^a	4.90 ± 0.09^a	4.80 ± 0.10^a
T3	3.30 ± 0.20^a	3.60 ± 0.18^a	3.60 ± 0.15^b	3.20 ± 0.17^b	3.40 ± 0.16^b	3.80 ± 0.14^b
T4	3.40 ± 0.18^a	3.70 ± 0.17^a	3.40 ± 0.16^b	3.40 ± 0.15^b	3.70 ± 0.18^b	4.00 ± 0.15^b

Data are presented as mean ± standard deviation. Means sharing different lowercase letters within the same row differ significantly according to the DMRT test at $p < 0.05$. T1: Treatment 1 (dadih West Sumatera from producer 1), T2: Treatment 2 (dadih West Sumatera from producer 2), T3: Treatment 3 (dadih Java from ori bamboo), T4: Treatment 4: (dadih Java from apus bamboo).

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Table 4: Lactic acid bacteria, yeast–mould counts, titratable acidity, and ph of dadih samples.

Treatment	Lactic acid bacteria (log10 CFU/g)	Yeast and mould (log10 CFU/g)	Titratable acidity (g lactic acid/100 g)	pH
T1	7.80 ± 0.10[b]	7.15 ± 0.04[a]	13.50 ± 0.20[b]	4.30 ± 0.04[c]
T2	8.10 ± 0.10[a]	7.20 ± 0.04[a]	15.00 ± 0.25[a]	3.80 ± 0.04[d]
T3	7.60 ± 0.10[c]	7.12 ± 0.04[a]	12.70 ± 0.20[c]	4.50 ± 0.04[b]
T4	7.30 ± 0.10[d]	7.00 ± 0.05[b]	8.00 ± 0.20[d]	5.50 ± 0.04[a]

Data are presented as mean ± standard deviation. Means sharing different lowercase letters within the same row differ significantly according to the DMRT test at $p < 0.05$. T1: Treatment 1 (dadih West Sumatera from producer 1), T2: Treatment 2 (dadih West Sumatera from producer 2), T3: Treatment 3 (dadih Java from ori bamboo), T4: Treatment 4: (dadih Java from apus bamboo).

Yeast and mould counts were relatively similar across treatments (7.00–7.20 log CFU/g), indicating that their contribution to the observed quality differences was minimal. However, the primary determinant of structural integrity. Treatments 3 and 4, which had higher pH values and lower acidity compared to Treatment 2, also exhibited reduced colour intensity (lower a* and b* values) and altered surface characteristics. These physicochemical conditions may influence light scattering and surface reflectance, explaining the differences observed in the CIELab analysis (Table 2) and their lower AI-based quality grading. The microbial and acidification profiles are closely linked to structural stability, colour attributes, and visual perception (Basdeki *et al*., 2025). These results indicate a close relationship between microbial activity, acidification, and visual characteristics of dadih. This supports the potential of the multimodal approach in capturing quality differences across treatments.

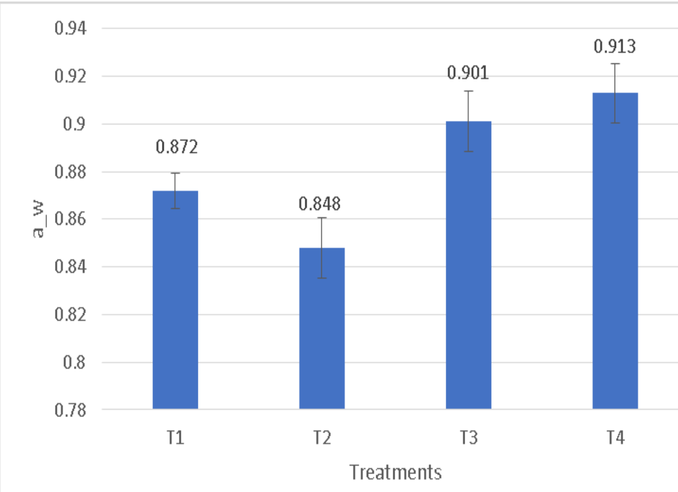

Figure 10: Water activity (a_w) of dadih samples under.

Different treatments.

Moisture availability, as reflected by water activity (a_w), differed markedly among treatments (Figure 10), indicating variations in water binding capacity within the fermented protein matrix. Treatment 4 recorded the highest a_w value (0.913), followed by Treatment 3 (0.901), whereas Treatment 2 showed the lowest value (0.848). These differences suggest that fermentation intensity and gel network development directly influenced the distribution between bound and free water fractions. The relatively low a_w observed in Treatment 2 is aligned with its higher lactic acid bacteria count and titratable acidity (Table 4), which may promote casein aggregation and the formation of a denser gel structure capable of entrapping water molecules more effectively. This structural compactness is likely associated with its favourable sensory scores and its classification as "Good" by the CNN-based (e-eye) system. In contrast, Treatments 3 and 4, which exhibited higher a_w values, likely contained a greater proportion of unbound water, contributing to increased whey separation and reduced structural uniformity. These characteristics were reflected in lower sensory ratings and their categorisation as "Fair" and "Poor" by the AI-based system. Elevated surface moisture may influence light scattering and reflectance, thereby affecting instrumental colour parameters, particularly the lower a* and b* values in Treatments 3 (a*=0.13 ± 0.06[d] and b*=15.37 ± 0.15[c]) and T4 (a* = 1.03 ± 0.12[c]; 14.60 ± 1.23[c]) compared to T1 and T2. These treatments also showed higher water activity (Figure 10) (T3=0.901 and T4=0.913) and syneresis intensity (T3=3.30 ± 0.20[a] and T4=3.40 ± 0.18[a]) along with lower scores in structural uniformity and overall appearance, indicating reduced structural stability and visual quality. This pattern supports their classification into lower quality categories by the AI-based system.

Contribution to sustainable development goals (SDGs)

This study improves the consistency of dadih quality evaluation through a more objective approach. It may support better processing control and reduced variability, which are relevant to responsible production (SDG 12) and innovation in food systems (SDG 9), although its broader impact depends on practical adoption (Asnayanti *et al*., 2025; Ridwan *et al*., 2026).

CONCLUSION

This study demonstrates that dadih from West Sumatra (T1 and T2) can serve as a practical reference for improving dadih production in Java. The multimodal evaluation showed that T1 exhibited the most desirable characteristics, including balanced colour parameters, stable acidification, moderate water activity, and high sensory acceptance, and was classified as "Excellent" by the CNN-based (e-eye) system. In contrast, the Java-produced dadih (T3 and T4) showed higher water activity, limited acidification (pH up to 5.50), and weaker structural stability, indicating incomplete fermentation. These conditions affected visual quality and resulted in lower AI-based classification. To improve product quality, fermentation should be carried out at 30–37°C for 24–48 hours. Milk type and processing conditions also influence fermentation and final product quality, so selecting appropriate raw materials is important. The combined use of instrumental, microbial, sensory, and AI-based evaluation provides a practical approach for identifying quality differences and supporting more consistent production.

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NOVELTY STATEMENT

This study introduces a multimodal framework for dadih quality evaluation by integrating CNN-based electronic eye analysis, CIELab colorimetry, sensory analysis, and physicochemical-microbial parameters. This approach provides a more objective, reproducible, and practical method to benchmark Java-produced dadih against traditional West Sumatran dadih.

AUTHORS'S CONTRIBUTION

AMW conducted the experiment, performed formal data analysis, curated the data, prepared the visualisation, and drafted the original manuscript. SHP, AM, HE, TES, and AS supervised the study, contributed to data interpretation, and participated in manuscript review and editing. RK and LER contributed to conceptualization and methodology development and participated in the final manuscript review and editing. All authors read and approved the final version of the manuscript.

Generative AI and AI-assisted technology statement

The authors declare that generative AI tools were not used to generate scientific content, data interpretation, or conclusions in this manuscript. AI-assisted tools were used only for language editing and clarity improvement, and all content was carefully reviewed and validated by the authors. The authors take full responsibility for the integrity and originality of the work.

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this article.

REFERENCES

Abedi E, Hashemi SMB (2020). Lactic acid production–producing microorganisms and substrates sources-state of art. Heliyon, 6(10): e04974. https://doi.org/10.1016/j.heliyon.2020.e04974

Anindita L, Chang J, Al-Rasjid GAPH, Rahmat E (2026). Characterization and health effects of functional bioactives from West Sumatra's fermented buffalo milk (dadih). Food. Chem. Adv., 10: 101210. https://doi.org/10.1016/j.focha.2025.101210

Arilla E, Martínez-Monzó J, Chiş MS, Fărcaş AC, Socaci SA, Codoñer-Franch P, García-Segovia P, Igual M (2023). Sensory evaluation, physico-chemical properties, and aromatic profile of pasteurised orange juice with resistant maltodextrin. Foods., 12(21): 4025. https://doi.org/10.3390/foods12214025

Arnold M, Rajagukguk YV, Gramza-Michałowska A (2021). Characterization of dadih: Traditional fermented buffalo milk of Minangkabau. Beverages., 7(3): 60. https://doi.org/10.3390/beverages7030060

Asnayanti A, Azizah S, Wati AM, Ridwan A, Dahlan AA, Asmara DR, Do ADT, Alrubaye A (2025). Incidence of bacterial chondronecrosis with osteomyelitis lameness in commercial duck flocks in Mojokerto, Indonesia. Animals., 15(24): 3632. https://doi.org/10.3390/ani15243632

Balasubramanian VK, Muthuramalingam JB, Chen YP, Chou JY (2024). Recent trends in lactic acid-producing microorganisms through microbial fermentation for the synthesis of polylactic acid. Arch. Microbiol., 206(1): 31. https://doi.org/10.1007/s00203-023-03745-z

Basdeki E, Vasilaki SE, Sensi M, Flemetakis E, Biscarini F, Power D, Tsironi T (2025). Reviewing the correlation of fish quality alteration and in-package headspace composition: evidence from a pH freshness indicator case study. Int. J. Food. Sci., 2025(1), 3576183. https://doi.org/10.1155/ijfo/3576183

Buckley RR, Giorgianni EJ (2023). CIELAB for color image encoding (CIELAB, 8-bit; domain and range, uses). In: Encyclopedia of Color Science and Technology. Springer., pp. 257–265. https://doi.org/10.1007/978-3-030-89862-5_14

Herlina VT, Setiarto RHB (2024). From tradition to innovation: dadih, the Minangkabau tribe's traditional fermented buffalo milk from Indonesia. J. Ethn. Foods., 11(1): 1–17. https://doi.org/10.1186/s42779-024-00234-6

Khalifa M, Albadawy M (2024). AI in diagnostic imaging: revolutionising accuracy and efficiency. Comput. Methods. Programs. Biomed. Update., 5: 100146. https://doi.org/10.1016/j.cmpbup.2024.100146

Kumar Y, Rahul K, Arora N, Gupta RP (2026). Computer vision technologies for food quality and safety assurance: evaluating trends and analytical results. Food. Anal. Methods., 19(2): 106. https://doi.org/10.1007/s12161-026-03019-6

Li Q, Zhao Z (2019). Acid and rennet-induced coagulation behavior of casein micelles with modified structure. Food. Chem., 291: 231–238. https://doi.org/10.1016/j.foodchem.2019.04.028

Lucey JA (2002). Formation and physical properties of milk protein gels. J. Dairy. Sci., 85(2): 281–294. https://doi.org/10.3168/jds.S0022-0302(02)74078-2

Melia S, Juliyarsi I, Kurnia YF, Pratama YE, Azahra H (2021). Examination of titratable acidity, pH, total lactic acid bacteria and sensory properties in whey fermented with probiotic Pediococcus acidilactici BK01. Adv. Anim. Vet. Sci, 10(1): 114–119. https://doi.org/10.3390/foods13132109

Phovisay S, Abdullahi AD, Kham NNN, Unban K, Shetty K, Khanongnuch C (2024). Microbial population and physicochemical properties of miang fermented in bamboo tubes by the Luar ethnic group in Lao PDR. Foods., 13(13): 2109. https://doi.org/10.3390/foods13132109

Pramana A, Yudhistira B, Jayalaksamana M, Kurnia D, Husnayain N, Pramitasari R (2025). Dadih, traditional fermented buffalo milk: a comprehensive review of the aspects of gastronomy, health benefits, and product development. J. Ethn. Foods., 12(1): 1. https://doi.org/10.1186/s42779-024-00261-3

Rachmawati A, Setyarini PH, Mahendra VI, Wati AM, Fajriani S, Ambayoen MA, Azizah S (2022). Aluminum oyster mushroom frying surface quality improvement through anodizing. Key Engineering Materials, 935: 49-54. https://doi.org/10.4028/p-65ldby

Ramaiyulis R, Nilawati N, Eva Y, Deby S, Budaraga IK (2021). Potential and development of incubation technology to improve the quality of "dadih" as a specific food of Minangkabau. Livestock Res. Rural. Dev., 33(7).

Ridwan A, Luni NZP, Azizah S, Wati AM, Rachmawati A, Djunaidi IH, Putri AR (2026). Strategic development of the Pelung chicken agribusiness system in a non-origin region: evidence from Malang Raya, Indonesia. Adv. Anim. Vet. Sci., 14(2): 364–377. https://doi.org/10.17582/journal.aavs/2026/14.2.364.377

Singh N, Sabrol H (2021). Convolutional neural networks-an extensive arena of deep learning: A comprehensive study. Arch. Comput. Methods. Eng., 28(7): 4755–4780. https://doi.org/10.1007/s11831-021-09551-4

Sirisathitkul Y, Dinmeung N, Noonsuk W, Sirisathitkul C (2025). Accuracy and precision of smartphone colorimetry: a comparative analysis in RGB, HSV, and CIELAB color spaces for archaeological research. STAR: Sci. Technol. Archaeolog. Res., 11(1): e2444168. https://doi.org/10.1080/20548923.2024.2444168

Sun J, Ren F, Chang Y, Wang P, Li Y, Zhang H, Luo J (2018). Formation and structural properties of acid-induced casein–agar double networks: role of gelation sequence. Food. Hydrocolloids., 85: 291–298. https://doi.org/10.1016/j.foodhyd.2018.07.030

Tamime AY, Robinson RK (2007). Tamime and Robinson's yoghurt: Science and technology. 3rd ed. Woodhead Publishing, Cambridge, UK.

Trigka M, Dritsas E (2025). A comprehensive survey of deep learning approaches in image processing. Sensors., 25(2): 531. https://doi.org/10.3390/s25020531

Wang Y, Cui X, Li Y, Wang S, Yan G, Zhang L, Li Y (2023). Effects of pH and ionic strength in calcium on the stability and aeration characteristics of dairy emulsion. Foods., 12(10): 1976. https://doi.org/10.3390/foods12101976

Wati AM, Lin MJ, Radiati LE (2022). Effect of different incubation time on goat's milk dadih on thorny bamboo (Bambusa stenostachya Hackel). JITEK., 17(2): 74–82. https://doi.org/10.21776/ub.jitek.2022.017.02.2

Young JA, Chang CW, Scales CW, Menon SV, Holy CE, Blackie CA (2024). Machine learning methods using artificial intelligence deployed on electronic health record data for identification and referral of at-risk patients from primary care physicians to eye care specialists: retrospective, case-controlled study. JMIR. AI., 3: e48295. https://doi.org/10.2196/48295

Zhao Z, Wang R, Liu M, Bai L, Sun Y (2025). Application of machine vision in food computing: A review. Food. Chem., 463: 141238. https://doi.org/10.1016/j.foodchem.2024.141238

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